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14. ABSTRACT   This project develops neural and computational models of the brain mechanisms that underlie human perception and cognition. It does this by mathematically characterizing and quantitatively simulating key brain mechanisms underlying higher-order human information processing as carried out within the laminar structure of the cerebral cortex. A model Laminar Computing paradigm promises to generate powerful information processing tools for dealing with large-scale problems. Perceptual projects model how the laminar circuits of visual cortex are designed to group distributed visual information into emergent object representations, to pay attention selectively to important information, and to learn their own optimal operating parameters in different visual environments. Cognitive processing projects model how the laminar circuits of inferotemporal and prefrontal cortex can rapidly classify, decide between, and predict noisy and potentially conflicting information in rapidly changing environments. The resulting models can be applied to technological problems in which the ability to autonomously visualize, learn, predict, and control information in rapidly changing environments is required. Testbed problems, including geospatial mapping and medical database analysis, have been developed in the context of the AFOSR-sponsored CNS Technology Laboratory.

15. SUBJECT TERMS
Neural computation, Neural networks, Adaptive Resonance Theory (ART), ARTMAP, Laminar Computing, Cognitive information processing, Visual cortex, Inferotemporal cortex, Prefrontal cortex, Parietal cortex, Basal ganglia

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May 15, 2001 – June 30, 2004

AFOSR F49620-01-1-0397

A unified brain architecture for perception and cognition with applications to information processing technology

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A unified brain architecture for perception and cognition
with applications to information processing technology

ABSTRACT

This project has developed neural and computational models of the brain mechanisms that underlie human perception and cognition. It does this by mathematically characterizing and quantitatively simulating key brain mechanisms underlying higher-order human information processing as carried out within the laminar structure of the cerebral cortex. A model Laminar Computing paradigm promises to generate powerful information processing tools for dealing with large-scale problems. Perceptual projects model how the laminar circuits of visual cortex are designed to group distributed visual information into emergent object representations, to pay attention selectively to important information, and to learn their own optimal operating parameters in different visual environments. Cognitive processing projects model how the laminar circuits of inferotemporal and prefrontal cortex can rapidly classify, decide between, and predict noisy and potentially conflicting information in rapidly changing environments. The resulting models can be applied to technological problems in which the ability to autonomously visualize, learn, predict, and control information in rapidly changing environments is required. Testbed problems, including geospatial mapping and medical database analysis, have been developed in the context of the AFOSR-sponsored CNS Technology Laboratory.

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AFOSR F49620-01-1-0397

A unified brain architecture for perception and cognition with applications to information processing technology

SUMMARY OF PROGRESS

During the term of the grant, funded researchers have made important progress on the major projects described in the proposed statement of objectives:

This project develops neural and computational models of the brain mechanisms that underlie human perception and cognition. It does this by mathematically characterizing and quantitatively simulating key brain mechanisms underlying higher-order human information processing, while also showing how these information processing capabilities are intimately linked to human learning abilities. Such information processing capabilities are carried out by the cerebral cortex. It is known that the cerebral cortex is organized into layers of cells, but how such "laminar computing" contributes to biological intelligence has been a mystery for almost a century. Our group has recently made significant progress in clarifying this mystery, and has hereby introduced the paradigm of Laminar Computing. This paradigm promises to generate powerful information processing tools for dealing with large-scale problems in which huge amounts of data from rapidly changing and noisy environments need to be learned, classified, predicted, and controlled. The present research models how such a laminar architecture is used in perception and cognition, and joins the two types of processes into a unified neural architecture for processing complex visually-based information. The perceptual projects model how the laminar circuits of visual cortex are designed to efficiently and rapidly group together distributed visual information into emergent object representations, to pay attention selectively to important information, and to learn their own optimal operating parameters in different visual environments. The cognitive processing projects model how the laminar circuits of inferotemporal and prefrontal cortex can rapidly classify, decide between, and predict noisy and potentially conflicting information in rapidly changing environments.

Once the algorithms that underlie these basic human competences are better understood, they can be applied to a large number of DoD and technological applications in which the ability to autonomously visualize, learn, predict, and control information in rapidly changing environments is required. Here the applications of geospatial mapping from remote sensing data and computer intrusion detection will be emphasized at first. The former application provides a challenging and important testbed for developing and evaluating the model's ability to preprocess, classify, and predict complex imagery. The latter application considers how to predict and control one of the most difficult databases in the world, and how to make decisions for intervention under demanding and time-sensitive conditions. These results will provide useful strategies for the design of better intelligent tutoring and instruction, and for the design of automated decision aids in situations where team decision making is needed in

demanding environments. In particular, understanding how the laws of grouping and attention work can provide useful insights into designing complex information displays. The lessons learned from the remote sensing and computer intrusion applications can help design automated assistants for prediction and decision-making in demanding environments.

These projects are being carried out in collaborations among the co-Principal Investigators and PhD students in the Department of Cognitive and Neural Systems (CNS) who are supported by the AFOSR grant. Integration of basic research with applied projects has been facilitated by the CNS Technology Lab, established in 2001 with support from by a grant (AFOSR F49620-01-1-0423 – Information fusion for image analysis: Neural methods and technology development) from the same AFOSR directorate. Many participating graduate students and faculty have contributed to project efforts in both science and technology, thus furthering the transportation of models across traditional barriers. Projects have been designed to take advantage of new capabilities for testing prototype designs on image-based problems, particularly problems of interest to users from the Air Force and industry. See
http://cns.bu.edu/techlab/modules/techtransfer/

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Gail A. Carpenter and Stephen Grossberg, co-PIs
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Names of PhD students and alumni of the Department of Cognitive and Neural Systems are underlined.

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SUMMARY OF RESEARCH PROJECTS

LAMINART: LAMINAR ARCHITECTURE OF VISUAL CORTEX
Research continued on developing a precise model, called the LAMINART model, of how and why the visual cortex, notably cortical areas V1 and V2, is organized into laminar circuits which compactly synthesize bottom-up, top-down, and horizontal connections. Such Laminar Computing: (1) enables stable development and perceptual learning to occur so that the cortex can build circuits that are matched to image statistics; (2) joins bottom-up data-driven processing with top-down attentional processing that can bias data-driven processing to emphasize high-level constraints; and (3) assures the analog coherence of distributed grouping, or binding, processes; namely, the coherent selection of correct groupings from noisy data without a loss of analog sensitivity. The model is called the LAMINART model because it shows how laminar cortical circuits work to achieve visual grouping while also incorporating attentional circuits that satisfy the ART Matching Rule of Adaptive Resonance Theory, or ART. Because all sensory and cognitive neocortical circuits share a similar laminar design, these results promise to generalize to many other forms of intelligent behavior, and to thereby provide a unified cortical design which is specialized to accomplish a wide range of perceptual and cognitive tasks by different parts of the brain. When this goal is realized, it will also lead to the design of a powerful class of general-purpose VLSI chips for biomimetically intelligent computation. Recent studies on the LAMINART model have been focusing on:

3-D VISION, FIGURE-GROUND SEPARATION, TRANSPARENCY, SYNCHRONY
In this set of projects, research is focusing on how the laminar circuits of visual cortex are organized to carry out 3-D vision, and how these mechanisms enable 2-D images to generate 3-D percepts in which objects are separated from one another, partially occluded objects are completed to facilitate later recognition processes, and 3-D surface representations are formed in cortical areas V1, V2, and V4. In particular, building on results from last year about how the brain carries out stereopsis and represents 3-D planar surfaces, a project was completed this year that builds upon these results by beginning to demonstrate how the visual cortex represents slanted and curved 3-D objects, and generates 3-D slanted and curved representations of 2-D pictures. This project incorporates mechanisms for 3-D grouping across multiple depths. It was gratifying to discover that the results from the LAMINART model about perceptual grouping naturally generalize to the 3-D case. This model is therefore called the 3D LAMINART model.

Most of the objects in the world are slanted or curved and span multiple depths with respect to an observer. Both binocular cues, such as disparity, and monocular cues, such as perspective, shading, and junctions, provide information about slant and tilt of an object. This article

proposes how the monocular and binocular cues are combined by the brain in a context-sensitive way to represent and perceive the 3-D structure of slanted and curved objects.

The results have broad implications for understanding how geometrical axioms of mathematics reflect how the brain actually represents 3-D surfaces. In particular, monocular cues taken by themselves can be ambiguous. There are many examples where two objects are made up of same set of surfaces, but depending on how the individual surfaces are combined, we perceive two completely different 3-D objects. The very same parallelogram can, for example, signal a flat, near-to-far, or a far-to-near slanted surface, depending upon the context. Contextual cues thus play a key role in disambiguating ambiguous local cues. In response to some 2-D images that can generate percepts of 3-D objects, such as Necker cube images, the percept can flip over time between two distinct 3-D representations of the object, and can be influenced by various factors such as attention.

Neurophysiological studies have found cells in extrastriate cortex to be tuned to features important in 3-D perception. In Macaque cortical area V2, cells are tuned to relative disparity, disparity edges, angles, border ownership, and figure-ground relations. There is also evidence for cells tuned to slanted 3-D boundaries in V4. Psychophysical studies have shown the importance of relative disparity, or disparity gradients, in human visual perception. This project developed a neural model of 3-D curved object representation wherein object fragments at multiple depth planes can be grouped together by disparity-gradient cells that are sensitive to an object's slant and tilt. These disparity-gradient cells can also form illusory contours in curved 3-D neon color displays. The model also includes cells that are tuned to angles and explains how disparity-gradient and angle cells can be self-organized by principles that have been previously been used to self-organize 2-D colinear bipole grouping cells. The model hereby proposes that the statistics of the visual environment help to determine the distribution of colinear bipole cells within one depth, colinear bipole cells across depths (disparity-gradient cells), and non-colinear bipole cells (angle cells) as variations of a single design theme of how horizontal connections form in cortical layer 2/3A. The model clarifies how monocular cues in an image, notably combinations of angles, can bias the activation of some disparity-gradient cells more than others to form a 3-D object representation in response to 2-D images, such as Necker cube images. Activity-dependent habituative mechanisms also occur in the model. Habituation is essential for the development of disparity-gradient and angle cells as well as of other properties of cortical cells. These habituative mechanisms can lead to multi-stable percepts when two or more 3-D interpretations of a 2-D image are approximately equally salient, as in Necker cube percepts.

This 3-D LAMINART model also explains how filling-in can be carried out across multiple depths. Grossberg and colleagues have proposed that the grouping of boundaries and the filling-in of surfaces are distinct, indeed complementary, processes. Whereas boundaries complete inwardly in an oriented fashion, surfaces fill-in outwardly in an unoriented fashion until a boundary is reached. These complementary processes are proposed to occur in the interblob and blob cortical processing streams through V1, V2, and V4. The outward filling-in process needs to be controlled across multiple depth planes when it fills-in 3D curved surfaces. A potential problem is that a multiple-depth boundary may have gaps at some depths, but not others, which

could allow spreading colors and brightnesses to spill out during filling-in. A related problem involved in filling-in of 3-D curved surfaces is clearly seen in 3-D illusory displays. Here the filling-in signal needs to spread in a controlled way across depths where there are no boundaries or filling-in inducers in the original images. The model clarifies how filling-in across multiple depths is controlled even if there are no boundaries in the inducing scene or image to contain it. This analysis also clarifies how a percept of a continuous change in depth can be achieved by a relatively small number of depth-selective surface representations.

The 3-D LAMINART model was further developed to explain how the visual cortex gives rise to 3-D percepts of stratification, transparency, and neon color spreading in response to 2-D pictures and 3-D scenes. These percepts probe issues concerning the constraints that determine whether percepts are opaque or transparent, and how 3-D boundary groupings control the flow of color during surface formation. Such percepts are sensitive to whether contiguous image regions have the same contrast polarity and ocularity. The model predicts how like-polarity competition at V1 simple cells in layer 4 may cause these percepts when it interacts with other boundary and surface processes in V1, V2, and V4. The model also explains how: the Metelli Rules cause transparent percepts, bistable transparency percepts arise, and attention influences transparency reversal. The constraint on V1 simple cells is consistent with earlier models of cortical development, and connects cortical development to adult perception in previously unsuspected ways.

Another project probed whether the laminar cortical model could quickly synchronize its processing during perceptual grouping. Perceptual grouping is well-known to be a fundamental process during visual perception, notably grouping across scenic regions that do not receive contrastive visual inputs. Illusory contours are a classical example of such groupings. Recent psychophysical and neurophysiological evidence have shown that the grouping process can facilitate rapid synchronization of the cells that are bound together by a grouping, even when the grouping must be completed across regions that receive no contrastive inputs. Synchronous grouping can hereby bind together different object parts that may have become desynchronized due to a variety of factors, and can enhance the efficiency of cortical transmission. Neural models of perceptual grouping have clarified how such fast synchronization may occur by using bipole grouping cells, whose predicted properties have been supported by psychophysical, anatomical, and neurophysiological experiments. These models have not, however, incorporated some of the realistic constraints on which groupings in the brain are conditioned, notably the measured spatial extent of long-range interactions in layer 2/3 of a grouping network, and realistic synaptic and axonal signaling delays within and across cells in the different cortical layers. This work addressed the question: Can long-range interactions that obey the bipole constraint achieve fast synchronization under realistic anatomical and neurophysiological constraints that initially desynchronize grouping signals? Can the cells that synchronize retain their analog sensitivity to changing input amplitudes? Can the grouping process complete and synchronize illusory contours across gaps in bottom-up inputs? Our simulations show that the answer to these questions is Yes.

The model is now being further extended to explain parametric data about binocular fusion and rivalry, as a probe of the cooperative-competitive and habituative mechanisms that are proposed to occur in the laminar circuits of cortical areas V1 and V2. It is also being developed to clarify how these laminar circuits can generate 3-D surface representations in response to realistic images, and how 3-D figure-ground processes are realized within the laminar circuits of cortical areas V1, V1, and V4 in order to make this possible.

SURFACE APPEARANCE AND FULL USE OF DYNAMIC RANGE
This study proposes how the visual cortex may process natural images under variable illumination conditions to generate surface lightness percepts, and how to apply these insights to develop new image processing algorithms. It is known that visual representations can adapt to a million-fold change in luminance. How does the visual cortex make generate surface representations that make full use of its dynamic range? Earlier work from our department has shown how the visual cortex can automatically normalize an image using context-sensitive interactions that compute relative measures of image reflectance. These results have been widely used in applications ranging from the processing of multispectral IR, SAR, and LADAR images to the design of new hardware systems for night vision, particularly in cooperation with our colleagues at MIT Lincoln Laboratory. These results did not show, however, how the visual cortex makes full use of its dynamic range.

A large psychophysical literature has shown that human percepts of surface lightness automatically adjust themselves to fully use the available dynamic range. This process is called lightness "anchoring." Many of these experiments show how the brain rescales image data so that the fullest possible range will be experienced, notably by determining what objects in a scene will look white, and rescaling other image lightnesses accordingly. Anchoring includes properties that go by the names articulation, insulation, configuration, and area effects. These anchoring properties help to make an image look natural even under dim moonlight and dazzling sunlight. An article is now being completed that clarifies mechanistically how anchoring occurs and quantitatively simulates the key anchoring data, as well as other classical and recent data about surface lightness and brightness perception, including discounting the illuminant, classical brightness constancy and contrast, Mondrian contrast constancy, the double brilliant effect, and the Craik-O'Brien-Cornsweet effect. The model is also consistent with a range of anatomical and neurophysiological data about how the the retina is organized to carry out early stages of context-sensitive light adaptation, and how the visual cortex may use boundary representations to gate the filling-in of surface lightness via horizontal cortical interactions. The model filling-in mechanism runs a thousand times faster than mechanisms of previous biological filling-in models, and thereby helps to clarify how filling-in can occur at the speeds shown in perceptual experiments. Because the surface processing system has complementary computational properties to those of the boundary processing system, these results are also providing new insights concerning the global organization of parallel processing streams in the visual cortex. The model has also been adapted into an image processing algorithm for computer vision to process complex natural scenes with anchored lightness properties.

DISTRIBUTED ART ARCHITECTURES AND CORTICAL MODELS

Winner-take-all coding generates maximally compressed categories, or pattern recognition codes, and allows ART networks to maintain stable learned memories. On the other hand, such maximal code compression can cause problems such as category proliferation when fast learning rates are used to learn a noisy training set. A new class of ART models that permit arbitrarily distributed code representations has been introduced. These distributed ART (dART) models generalize winner-take-all ART models. In particular, in the special case of winner-take-all coding and fast learning, the unsupervised dART model reduces to fuzzy ART. dART automatically apportions learned changes according to the degree of activation of each coding node, which permits fast as well as slow learning with compressed or distributed codes. Distributed ART models replace the traditional neural network path weight with a dynamic weight equal to the rectified difference between coding node activation and an adaptive threshold. Dynamic weights that project to coding nodes obey a distributed instar learning law and those that originate from coding nodes obey a distributed outstar learning law. Inputs activate distributed codes through input-dependent and input-independent signal components with dual computational properties, and a parallel distributed match-reset-search process helps stabilize memory. Model development is a process of balance and resolution of potentially competing design tradeoffs, with themes that include prototype vs. exemplar learning, inflexible vs. transient memories, feedforward vs. feedback connectivity, bottom-up vs. top-down signal processing, fast vs. slow adaptation, and localist vs. distributed code representations. The emerging synthesis may be characterized as *quasi-localist* learning. Ongoing projects are investigating new model architectures, which are both inspired by physiological data and designed to improve performance on application benchmarks. An open problem which we have begun to tackle concerns how the inferotemporal and prefrontal cortices realize distributed category learning codes; see below.

SIMULATING HUMAN DATA ABOUT OBJECT CATEGORIZATION

An article is now being written up that proposes a solution to the following basic problem in cognitive science and intelligent data base management: What information is bound together into object or event representations? Some scientists believe that exemplars, or individual experiences, can be learned and remembered by humans, like those of familiar faces. Unfortunately, storing every exemplar that is ever experienced during life can lead to a combinatorial explosion of memory, as well as to unwieldy memory retrieval. Others believe we learn prototypes that represent more general properties of the environment, such as that everyone has a face. But then how do we learn specific episodic memories? Correspondingly, in the cognitive literature on recognition, and more specifically on object categorization, these two types of descriptions have lead to prominent models of the human categorization process. In the prototype-based approaches, a single center of a category is extracted from many exemplars, to-be-categorized items are compared to these category prototypes, and they are assigned to the category of the most similar prototype. The alternative exemplar-based approach does not assume a single category center. Instead, a more distributed representation of the category domain is assumed to exist, wherein memorized sets of individual exemplars are the core representational units in memory. A new item is compared to each of the exemplars and similarity measures are obtained in terms of these comparisons.

Both of these approaches have advantages and disadvantages. Because the exemplar approach codes individual events, it is plausible that individual events, like a particular face in a particular pose, can be recognized. On the other hand, this approach raises the problem of how to recognize novel variations of familiar events; that is, where should category boundaries be drawn? Said more generally, how can one determine the proper level of abstraction when all that is stored are exemplars? In addition, how can one search such a large memory in an efficient way. How can one avoid the combinatorial explosion as more and more exemplars are learned and searched as life proceeds? In particular, why does not the reaction time for a recognition event increase dramatically with the total number of exemplars that are stored in memory?

Because prototypes code abstractions of multiple events, it is plausible how the learning abstract information, such as the fact that all humans have a face, may occur. On the other hand, then one is faced with the problem of how to recognize individual events, such as the particular face of a friend. Here, too, the problem of abstraction is again raised, but from the opposite end of the concreteness-abstractness continuum.

In order to deal with these concerns, a third approach, which often is called the *rule-plus-exceptions* model, was developed to attempt to incorporate the strengths of both the exemplar and prototype approaches, while overcoming their most obvious weaknesses. Here it is assumed that categories are represented mainly by prototypes but, in addition, it allows the existence of few exemplars that are located usually at points very distant from the category centers or in regions where class boundaries based on distance from prototypes would give erroneous results. Despite the significant progress represented by these three modeling approaches, they all experience several basic difficulties. A key difficulty is that all the models take the form of formal equations for response probabilities. None of them actually learns their exemplars or prototypes using the type of real-time incremental learning process that humans experience. They all define prototypes *a priori* even though these prototypes might not be the ones that are actually used by human subjects. None of these models explains how exemplar or prototype information may be stored or retrieved as part of an information processing dynamic. In particular, the successful exemplar models all use combinations of exemplars, not individual exemplars, to derive formal response probabilities, but the actual process whereby these combinations are derived from stored individual exemplars is not specified. Finally, none of these models sheds light upon the types of brain categorization processes for which neurophysiological data have been accumulated in cortical areas like inferotemporal cortex, or IT, from awake behaving monkeys as they learn and perform categorization tasks.

The present project results propose how to resolve these long-standing problems through the use of a distributed ART model. This ART model suggests how *critical feature patterns* (CFP) may be learned in real time by an individual learning subject. Depending on the structure of the learning environment, such a CFP may encode general information, such as a prototype, or specific information, such as an exemplar. Typically, combinations of prototypes and exemplars will be learned to recognize a particular event, much as in the rule-plus-exceptions model. One class of thirty human cognitive experiments has been used to test conflicting views in the

prototype-exemplar debate. In these experiments, during the test phase, subjects unlearn in a specific way the old items that they had learned to categorize perfectly in the training phase. Cognitive categorization models have not yet described how such categories are learned or forgotten through time. In this project, an ART model is used to learn categories in response to these experimental stimuli. The simulation results agree with experimental data, achieving perfect categorization in training and a good match to the pattern exhibited by human subjects in the testing phase.

This research on category learning did not focus on how model processes are embedded within the laminar circuits of neocortex. A related project is now exploring how the laminar circuits of inferotemporal cortex carry out cognitive tasks, notably how object categories are learned within the laminar circuits of IT. This project will attempt to show how the laminar circuits of inferotemporal cortex can simulate the learned recognition performance of human subjects on these benchmark cognitive data. When these results are completed, they will be joined with those from the next project to model spatially-invariant recognition properties that emulate human performance using a laminar inferotemporal cortical model. The system will then be specialized for large-scale recognition tasks. A related project is modeling how recognition categories work together with horizontal grouping properties to generate better benchmarks for recognition of textured scenes.

SIMULATING HUMAN DATA ABOUT COGNITIVE INFORMATION PROCESSING
Another project at a still higher cortical level is developing a laminar model of the prefrontal circuits for temporary storage of sequences of events in working memory, and for learning to recognize temporal sequences of events. This analysis is beginning to show how the laminar circuits that are used for filtering and grouping within visual cortex are specialized for higher cognitive tasks in prefrontal cortex. This model will be developed to quantitatively explain and simulate a large data base about human cognitive information processing. These data probe important processes concerning how humans learn to cognitively process events that occur sequentially in time, notably how working memory, cognitive plans, and individual subject strategies learn to work together to carry out sequence-sensitive information processing. Data concerning the limited temporal extent of working memory, the bowing of the serial position curve, error profiles, temporal grouping effects, presentation speed effects, list and word length effects, phonemic similarity effects, nonword lexicality effects, word frequency, item familiarity, and list strength effects, and distractor paradigms are being simulated. When the biological part of the project is finished, then the system will be specialized for large-scale applications.

FAST VISUAL SEARCH OF CLUTTERED SCENES
Humans are extremely good at searching cluttered scenes for desired targets. A large experimental literature has accumulated to demonstrate properties of how humans search for targets amid distractors. Grossberg, Mingolla, and Ross published a model in *Psychological Review* in 1994 to quantitatively explain and simulate many of the most challenging data concerning how this happens. That article developed a search algorithm which proposed how four types of processes should interact together in order to search efficiently: how visual boundaries and surfaces are formed, how visual object categories are learned and attended, and

how spatial attention works. Although quantitative data fits were achieved, the model was merely an algorithm that could not process realistic imagery in real time.

This project is building on these algorithmic insights to develop a neural architecture that operate in real-time to process imagery using interacting circuits for boundary, surface, category, and spatial processing. In particular, this new work has begun to clarify how different parts of the inferotemporal cortex, notably IT anterior and IT posterior, work together to learn spatially-invariant 3D object categories through incremental on-line learning. These spatially-invariant object categories in IT cortex are part of the brain's What processing stream, which processes what targets are in the world. In so doing, it eliminates information about where these targets are in space, so that a combinatorial explosion is not caused by coding all positions, sizes, and orientations of a single object. Spatial information cannot be totally discounted, however, because it is needed to act upon objects once they are recognized. Spatial information is processed by a complementary Where processing stream that passes through the parietal cortex. Work is continuing on how to combine both sorts of information via What-Where fusion into an architecture for visual search of cluttered scenes that can handle realistic imagery. This architecture is incorporating perceptual representations of 3D boundaries and surfaces, spatially-invariant object categories of What the targets are, and spatial representations of Where the targets are. For example, new ideas are being developed about how spatial attention is allocated to allow a spatially-invariant 3D object category to be learned, and about how, once it is learned, it can nonetheless access the spatial coordinates of the object for purposes of acting upon it.

REACTIVE AND PLANNED EYE MOVEMENTS DURING VISUAL SEARCH

A key challenge to intelligence is to balance reactive and planned behaviors. Rapid reactive movements are needed to ensure survival in response to danger. But impulsive behaviors that are not appropriate in a given context can prevent learning of task-appropriate, planned behaviors that can earn rewards. Planned movements take longer to elaborate, and are often less directly supported by current stimuli. How can a learned plan compete effectively with an otherwise faster reactive movement before the plan is fully elaborated? How can plans be learned on-line from combinations of more primitive reactive behaviors? In particular, how can appropriate planned eye movements be executed in response to a complex scene during visual search?

This project is developing a detailed neural model that clarifies such issues, which are as important for understanding how planned movements are learned as they are for general cognition. A first article based on the project is now in press. Eye movements provide a paradigmatic case for studying these issues for several reasons: They have been well-studied; they involve visuo-cognitive-motor transformations that are used in many types of learned behaviors; and they are crucial for understanding how more complex cognitive behaviors are learned and performed, including reading and paying attention selectively to information that must be learned, recognized, and acted upon to achieve success. Questions for which answers are developed in the model are: How does the brain prevent reactive eye movements from being triggered in situations where a more slowly selected planned movement would be more adaptive? How can learning convert a visual stimulus into a discriminative cue to look elsewhere for anticipated rewards? How does the brain run an internal competition between alternative

plans? How can the brain prevent a premature attempt to perform several plans before a coherent single plan emerges from the internal competition? What resources does the brain have for representing plans in different ways that may be more or less appropriate for different tasks? How does it learn to use the best plan representation? How does reward history act currently, in interaction with current desires, to bias the plan competition? Key features of both reactive and planned movements are learned using broadly distributed brain sites that are often co-activated, ranging from the basal ganglia, superior colliculus, and cerebellum to the temporal, parietal, premotor and prefrontal cortices. To realize these properties, a movement gate opens quickly to enable fast reactive movements to occur if no competing plans are available, yet can also block reactive movements when a context-appropriate plan is being elaborated until the plan is selected and can open its gate to launch a different movement. As environmental contexts change, this gating system rapidly re-configures itself to perform the task appropriate in the current context.

The model proposes how strategy priming and action planning (in cortical layers III, Va and VI of the frontal eye fields) are dissociated from movement execution (in layer Vb), how the basal ganglia help to choose among and gate competing plans, and how a visual stimulus may serve either as a movement target or as a discriminative cue to move elsewhere. The direct, indirect and hyperdirect pathways through the basal ganglia are shown to enable complex gating functions, including deferred execution of selected plans, and switching among alternative sensory-motor mappings. Notably, the model can learn and gate the use of a What-to-Where transformation that enables spatially invariant object representations to selectively excite spatially coded movement plans. Model simulations show how dopaminergic reward and non-reward signals guide monkeys to learn and perform saccadic eye movements in the fixation, single saccade, overlap, gap, and delay (memory-guided) saccade tasks. Model cell activation dynamics quantitatively simulate the neurophysiologically recorded dynamics of seventeen cell types during performance of these tasks.

INFORMATION FUSION AND HIERARCHICAL KNOWLEDGE DISCOVERY BY ARTMAP NEURAL NETWORKS

Classifying novel terrain or objects from sparse, complex data may require the resolution of conflicting information from sensors working at different times, locations, and scales, and from sources with different goals and situations. Information fusion methods can help resolve inconsistencies, as when evidence variously suggests that an object's class is *car*, *truck*, or *airplane*. Novel methods consider a complementary problem, supposing that information from sensors and experts is reliable though inconsistent, as when evidence suggests that an object's class is *car*, *vehicle*, and *man-made*. Underlying relationships among objects are assumed to be unknown to the automated system or the human user. The ARTMAP information fusion system uses distributed code representations that exploit the neural network's capacity for one-to-many learning in order to produce self-organizing expert systems that discover hierarchical knowledge structures. The system infers multi-level relationships among groups of output classes, without any supervised labeling of these relationships. The procedure has been illustrated with several image examples, and with a pilot study of knowledge discovery in a medical database application.

TECHNOLOGY TRANSFER AND THE CNS TECHNOLOGY LAB
SUMMARY OF ART-BASED TECHNOLOGY TRANSFERS

SUMMARY: ART-BASED PRODUCTS FROM AMERICAN HEURISTICS CORPORATION (AHC)
During the 1980s, AFOSR funded the first working Adaptive Resonance Theory (ART) models, which implement real-time recognition, search, learning, and prediction. Two complementary AFOSR grants for basic and applied research currently support continuing ART system development and technology transfer in the Boston University Department of Cognitive and Neural Systems (BU/CNS). A recent customer for this evolving technology is the American Heuristics Corporation (AHC), whose web site (www.heuristics.com) describes two ART-based algorithms, Adaptive Fuzzy Feature Map (AFFM) and Adaptive Temporal Correlation Network (ATCN), as the foundation of the company's core technology, "THOT®." AFFM and ATCH provide the large-scale data mining capabilities for AHC products and services, which include personnel and audit screening systems for government and commercial clients.

WHAT WAS ACCOMPLISHED: BU/CNS NEURAL NETWORK TECHNOLOGY TRANSFER
Sites of early and ongoing transfer of ART-based technology include industrial venues such as the Boeing Corporation and government venues such as MIT Lincoln Laboratory. A recent report on industrial uses of neural networks (Lisboa, 2001) states that the Boeing Neural Information Retrieval System "is probably still the largest-scale manufacturing application of neural networks. It uses [ART] to cluster binary templates of aeroplane parts in a complex hierarchical network that covers over 100,000 items, grouped into thousands of self-organised clusters. Claimed savings in manufacturing costs are in millions of dollars per annum." At Lincoln Lab, a team led by Waxman developed an image mining system which incorporates several BU/CNS models of vision and recognition. Over the years a dozen CNS graduates (Aguilar, Baloch, Baxter, Bomberger, Cunningham, Fay, Gove, Ivey, Mehanian, Ross, Rubin, Streilein) have contributed to this effort, which is now located at Alphatech, Inc. (www.alphatech.com). Customers for BU/CNS neural network technology attribute their selection of ART over alternative systems to the model's defining design principles. In listing the advantages of its THOT® technology, for example, AHC cites several characteristic computational capabilities of this family of neural models, including fast on-line (one-pass) learning, "vigilant" detection of novel patterns, retention of rare patterns, improvement with experience, "weights [which] are understandable in real world terms," and scalability.

WHY IT IS IMPORTANT: LARGE-SCALE ADAPTIVE DATA MINING FOR GOVERNMENT AND INDUSTRY
The AHC web site describes products derived from ART-based THOT® technologies as follows: "The **Adaptive Fuzzy Feature Map (AFFM)** is a self-organizing system that is used to look at large amounts of data and detect patterns within that data. Its feature set is rich and makes it unique in the data mining and pattern recognition worlds. The **Adaptive Temporal Correlation Network (ATCN)** adds a temporal component to features of the AFFM. It looks at data across several different data streams and helps the user locate patterns of activity in one data stream that may be predictors of activity in another! Other products we have developed, into

which the above and other intelligent technologies have been imbedded, include: **Profiler**, a pre-employment screening system, helps employers locate applicants most like their proven successful employees. **PiCard** is used by the procurement card industry to help users locate card activity that would be considered of interest to the institution. **ICIAS** (Intelligent Case Identification and Allocation System) is utilized by the tax and revenue industry for identifying cases of interest and allocating resources by applying the best individual for that particular audit." Customers for these new products include government agencies and contractors: Computer Sciences Corp, Dept of Treasury, Electronic Warfare Asso (EWA), FBI, IRS, Lockheed Martin, ManTech, Military Sealift Command (MSC), NASA, NSA, National Technology Transfer Center (NTTC), Raytheon, SAIC, State of California, and WV Workers Comp Fund; and commercial users: Aristar Corp, Bank of Hawaii, Bayer Intl, CoreStates Bank, Deloitte & Touche, Equifax Risk Mgt Services, Mobay Chemical Corp, SAL Chemical, and Univ of Illinois.

BU/CNS Technology Transfer Customers

American Heuristics Corporation (AHC), Triadelphia, WV, Roland L. Hobbs, (304) 547-4201 ext 14. www.heuristics.com

Charles River Analytics, Cambridge, MA, Magnus Snorrason, (617) 49103474 ext 524. www.cra.com

Accurate Automation, Chattanooga, TN, Robert Pap, (800) 777-9974. www.accurate-automation.com

Sonetech Corp. Maryland Technology Center, Bedford, NH, Raymond Sosnowski, (301) 570-4901. www.sonetechcorp.com

Boeing Corporation, Seattle, WA, Scott D.G. Smith, (425) 865-3591. www.boeing.com/flash.html

National Library of Medicine (NLM), Bethesda, MD, George Thoma, (888) 346-3656. www.nlm.nih.gov

Orion Engineering Corp., Westford, MA, Herbert J. Sinnock, (617) 625-3953. www.orionengineering.com

Research Results

Large-scale data mining products and services for government (including FBI, IRS, NASA, NSA) and commercial customers.

ART technology embedded in several products; for the Air Force: ATR (vehicles) from multi-sensor data, including LADAR and laser vibrometry.

Logistics application used by Navy and Marines: prediction of event combinations in scheduling scenarios.

Air Force implementation: identification of acoustic signatures in noisy environments.

Neural Information Retrieval System for large-scale parts clustering software in design and manufacturing CAD systems.

ART networks used for wavelet-based adaptive vector quantization for high fidelity compression and fast transmission of Visible Human color images.

Energy controller for small-scale users: Distributed Energy Neural Network Integration System (DENNIS™).

Defense Science Technology Organization, Salisbury, Australia, Peter Lozo. www.dsto.defence.gov.au

Center for Remote Sensing, Boston University, Sucharita Gopal, (617) 353-5744. www.bu.edu/remotesensing

Reyrolle Protection, Hebburn, Tyne & Wear, UK, +44 (0) 191 401 5277

Immunetics, Cambridge, MA, (617) 492-5416. www.immunetics.com

MIT Lincoln Lab, Lexington, MA 02420, Randy Avent,(781) 981-7453

NIMA/NTA, Jeff Kretsch, (703) 262-4554.

Air Force Rome Lab / Information Fusion, John Salerno.

Fuzzy rule-based fusion technique for surface landmine detection from multispectral and texture bands.

ART-VIP (Visualization and Image Processing) software for land cover classification and analysis.

Fault diagnosis in multicircuit transmission lines.

Automated medical testing, e.g., for Lyme disease (SBIR).

Recognition engine and feature selection methodology for image-based information fusion and data mining system.

NIMA/NTA software implementation by Waxman et al., working in the CNS Technology Lab.

AFRL/IF software implementation by Waxman et al., working in the CNS Technology Lab.